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Research article

An optimization method for energy structures based on life cycle assessment and its application to the power grid in China

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ABSTRACT

The optimization of energy structures, aimed at saving energy and reducing emissions, is an important precautionary measure against climate change. This study considers different environmental impacts of power systems, and investigates ways to optimize power structures and decrease their potential environmental impact. A multi-objectives optimization model of energy structures was created based on life cycle assessment (LCA). This model covers several environment impacts, rather than only focusing on carbon emissions. LCA was used to calculate the different environmental impacts and provided a new method for normalization. The model was applied to the power industry in China. Three kinds of environmental impacts were considered: material input (MI), global warming potential (GWP), and water deprivation (WD). The five major existing methods of electricity generation in China were considered: thermal power, nuclear power, hydro power, wind power, and solar photovoltaic power. The system boundary included all life cycle stages; specifically, extraction of raw materials and resources, production, energy generation processes, and power transport. The optimization results showed that the total environmental impacts were reduced; MI, GWP, and WD were decreased by 29.53%, 29.67%, and 19.06%, respectively. This method provides new insights into optimization of energy structures by considering multi-environment impacts.

1. Introduction

The demand for energy continues to increase in many countries (Arto et al., 2016); accordingly, the issues caused by energy use also continue to increase. The optimization of energy structures, leading to energy saving and reduction in emissions, is an important precautionary measure against climate change (Bhattacharyya, 2012; Liu et al., 2013), especially in China. Coal is the major power source in China, and electricity is primarily obtained from thermal power. The country's development plans now focus on the optimization of energy structures for the future. The 13th Five-Year Plan of Power in China dictates that the generation of renewable, non-fossil sources of power should be increased to 31% by 2020 (NEA, 2016). The plan also states that the amount of non-fossil fuels and natural gas used should be increased by 2.6% and 1.9%, respectively, by 2020 (NEA, 2016).

In addition to the energy strategy, a large amount of studies on energy structure optimization have been published. Initially, studies focused on energy prediction. Related influential factors have been considered, including economic development, population, price of energy, urbanization, etc. (Yang and Shi, 2017). Later studies have considered energy optimization in the context of both influential factors and associated problems, especially environment pollution. Related to environmental impacts, greenhouse gas (GHG) emissions have become an increasingly prominent issue. China has enthusiastically been participating in environmental emissions reductions; in particular, reducing carbon emissions has become a major target for the optimization of energy structures (Ou et al., 2011).

The pinch analysis method has been used for energy structure optimization with carbon constraints (Atkins et al., 2010; Walmsley et al., 2015). Pinch analysis techniques have been developed for a wide range of applications, from thermal processing plants or water integration to financial and supply chain management. The pinch analysis method can be used for a single overall emissions target or for cases where separate sectors or geographic regions have distinct targets but share a common energy resource (Tan and Foo, 2007). Several researchers have used pinch analysis for energy sector planning and sustainable power generation (Lee et al., 2009; Tan et al., 2009).

However, another method, the multi-objectives optimization method, is suitable for use when several objectives are considered for optimization. In this situation, we can set several goals. When using multi-objectives optimization method, the multi-objectives should be changed to one single objective in order to simulate the optimization results. Other methods can also be used for construction of optimal

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energy planning models, such as the general source–sink concept, process integration methods, mixed integer linear programming, etc. (Pękala et al., 2010; Krishna Priya and Bandyopadhyay, 2017).

The multi-objectives optimization method is most suitable for resolving real life problems related to projects and management. Some of the objectives may be contradictory, which makes decision making difficult. The multiple objectives of energy structure optimization include: meeting the requirements of the economy, saving on the cost of energy consumption, and reducing carbon emissions. These objectives should be converted to a single objective using a weighting method (termed "normalization" in this study), such as the constraint method, the synthetic method, or the multiple-targets planning method. The weighting method is used to convert different objectives to a cost price when performing multiple objective energy optimization (Krishna Priya and Bandyopadhyay, 2017). However, the cost price changes over time and varies across regions, which can lead to a certain level of uncertainty.

Therefore, new normalization methods are required. In addition, the carbon emissions during the energy usage stage are generally focused when performing energy structure optimization; carbon emissions from other life cycle stages such as fossil fuel production, transportation are not considered. Life cycle assessment (LCA) addresses these limitations. First, carbon emissions based on LCA can systematically reflect the characteristics of energy, providing more complete and accurate data for energy optimization and reformation. Second, it also can provide mature and universal normalization and weighting method.

Additionally, LCA can cover more environment impacts rather than only focusing on carbon emissions. Energy is both a large source of carbon emissions and a key industry that requires resource inputs such as materials and water.(Garcia et al., 2014; Gallagher et al., 2015; Hertwich et al., 2015). The energy industry has used up to 50% of the total coal sources in China, totaling over 1.85 billion tons in 2015 (NBOC, 2016); it has also consumed large amounts of water resources, i.e., ~16 billion m^3 (Gao, 2012). Therefore, carbon emissions should not be the only factor considered; other important environmental impact factors should also be considered in energy structure optimization.

Therefore, this study has created an optimization approach for energy structures that considers several environment impacts and covers the life cycle stages of energy supply. This approach was then applied to power structures in China in order to investigate ways in which to optimize Chinese power structures and decrease their potential environmental impacts. This study serves to motivate energy optimization studies restricted by environmental factors and also serves as a theoretical basis for the sustainable development of power systems.

2. Methods and data

2.1. Framework

The purpose of this study was to create an optimization model for energy structures with consideration for different kinds of environmental factors; the aim of the model was to minimize the overall environmental impact of energy structures. LCA was used for evaluating different environmental impacts and for normalization of the environmental impacts. Matlab7.0 was used in our study for this model operation (see Fig. 1).

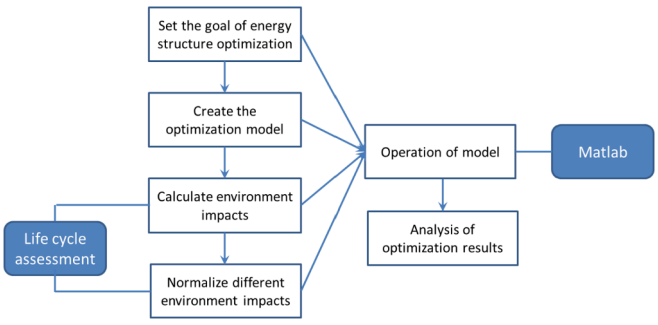

Fig. 1. The framework for this study.

There were two steps involved in model building. The first was to set the objectives. The second was to create the math model for the optimization. A multi-objectives model was investigated in this study. The most important aspect of this model is the selection of a method for converting different environment impacts into one factor. In our study, LCA was used for this purpose.

2.2. The objectives of the model

Two kinds of objectives in this study were focused on. The first was related to the energy system. Specifically, the amount of energy after optimization must not be less than the required amount of energy. The second was related to the environment impacts. Specifically, the total sum of all environmental impacts must be as small as possible, and every environmental impact must be less than before optimization.

2.3. Establishing the optimization model

In this study, the variables in the energy structures are energy element 1 (A), energy 2 (B), energy 3 (C) … energy N (N), where the energy values prior to optimization are (A*, B*, ⋯ N*). For the first type of environmental impact, the supply units of energy 1, energy 2, … energy N are (X_1, X_2, …Xn), respectively; for the second type of environmental impact, the values of the different resources are (Y_1, Y_2, … Yn), respectively, and so on, where for the Nth type of environmental impact, the values of the different resources are (N_1, N_2, …Nn), respectively.

The target optimization model follows this form:

The total of the first environmental impact is $F_1 = A \times X_1 + B \times X_2 + \cdots + N \times Xn$.

The total of the second environmental impact is $F_2 = A \times Y_1 + B \times Y_2 + \cdots + N \times Yn$.

The total of the Nth environmental impact is $F_N = A \times N_1 + B \times N_2 + \cdots + N \times Nn$.

The total environmental impact is $F = F_1 + F_2 + \cdots F_N$.

There are several restrictions on the model. The variables in the optimization model must fulfill the following requirements:

(1) The total amount of the different kinds of power must satisfy the power consumption requirements; therefore, A + B + C+ … +N = energy requirement.
(2) When considering limiting factors such as resource endowment, social safety, cost etc., the values of the factors should satisfy the limitations of the development of different resources. In other words, A∈ [Amin, Amax], B∈ [Bmin, Bmax] ⋯ N∈ [Nmin, Nmax].
(3) Each environmental impact after optimization must be less than that prior to optimization ($F_1 < F_1^*$, $F_2 < F_2^*$,⋯Fn < Fn*).

The ultimate goal of this model is that, under these three outlined restrictions, the value of the target function F is minimal, and the calculation of the values for each variable yields an energy ratio for optimization.

2.4. Normalization

During optimization, the different environmental impacts should be adjusted to a common unit to achieve the minimum total possible. Eco-indicator 99, a life cycle environmental impact method, was used in our model (Goodkoop, 1999).

Eco-indicator 99 is a widely used LCA method with a relatively developed methodological system. This methodological system uses ecological indicators for the ultimate evaluation of environmental

impact, where end-point environmental impacts include damage to human health, damage to ecological system quality, and resource destruction. The mid-point environmental impacts determined include human toxicity, global warming potential (GWP), ionizing radiation, ozone depletion, respiratory system effects, acidification, water eutrophication, ecotoxicity, land use, fossil fuel usage, and mineral mining.

Eco-indicator 99 was used to quantify the impact factors in three steps: (1) calculation of pollutant emission or resource consumption type based on data analysis results, i.e., categories of mid-point environmental impact; (2) normalization of damage factors of different types of damage, i.e., the effects of ultimate environmental impacts on resources, human health, and ecosystems; (3) calculation of a single ecological index value by weighting three factors of environmental impact: ecosystem destruction, damage to human health, and resource depletion. Therefore, our ecological indicator value was calculated as a unified unit (Pt) based on the three types of environmental impacts. The use of Eco-indicator 99 enables the quantification of ecological indicators, where the ecological indicator values reflect the severity of environmental pressures caused by the product systems in question.

3. Application of optimization model

The optimization model was then applied to the power grid in China. The five major existing methods of electricity generation in China were considered: thermal power, nuclear power, hydro power, wind power, and solar photovoltaic (PV) power (hereafter termed “solar power”). The system boundary included all life cycle stages: extraction of raw materials and resources, production, energy generation processes, and power transport.

3.1. Determination of environmental impact

The environmental impacts in this study included GWP, material input (MI), and water deprivation (WD). Carbon emissions from energy are the main source of GWP. GWP has become an issue of international relevance and is an important limiting factor in increasing energy supply capacity (Hertwich et al., 2015). Therefore, we used GWP as our first target parameter. LCA (ISO, 2006) was used to account for GWP.

The environmental impacts of human activity are largely determined by the natural resources used, the amount and quality of materials entering the economic system, and the amount and quality of waste material entering the environment through the economic system. The environmental disturbance caused by the former leads to resource depletion and ecosystem degradation, and the latter leads to environmental pollution. Ecosystem pressure caused by power systems is a result of the exploitation of natural resources and materials, as well as their transport and consumption. Therefore, it is important to consider the MI of a power system. We selected LCA as our core calculation method, with consideration for both resources and total material investment, using quality as the basic unit.

The relationship between water resources and energy resources is becoming increasingly interwoven, and water resources have become a major limiting factor in energy development. The water footprint is an indicator of water consumption and pollution in energy systems (Hoekstra et al., 2011); therefore, we considered the environmental impact of WD based on the water footprint as an important factor in the adjustment of energy structures.

3.2. Optimization model application

The power grid optimization model was built according to the method described above, as depicted in Table 1. The five types of power generation methods are denoted A, B, C, D, and E, respectively, and the three types of environmental impacts, including MI, GWP, and WD, are denoted as x, y, and z, respectively.

The three restrictions in the optimization of power structures were:

(1) The total amount of the five power generation methods should satisfy the electricity consumption in 2012; A + B + C + D+E = total consumption in 2012, i.e., 49859.15 hundred million kWh.
(2) On the basis of limiting factors such as resource limitations, social safety, etc., developmental requirements of different resources must be met.

According to the upper and lower ranges of the predictions, we designated restrictions for the adjustment of different resources. According to previous data analysis (Liu et al., 2013; Ye, 2010), A∈[55.16%, 78.47%], B∈[11.28%, 17.16%], C∈[0.07%, 3.46%], D∈[1.97%, 22.52%], and E∈[2.06%, 7.57%].

(3) The environmental impacts must be decreased after optimization ($F < F^*$). In other words, the three types of environmental impacts of the power structures after optimization must not exceed those prior to optimization; specific environmental factors must not be sacrificed in order to reduce other impacts.

The ultimate goal is to achieve the minimal possible total of the five types of power and the three types of environmental impact factors.

3.3. Environmental impacts based on LCA

3.3.1. System boundary

The environmental impacts of power were calculated across all life cycle stages. The system boundary included all life cycle stages: extraction of raw materials and resources, production, energy generation processes, and power transport; 1 kWh was chosen as the function unit. The system boundaries of the five kinds of power are shown in Fig. 2.

3.3.1.1. System boundary of thermal power. The system boundary of thermal power included primary energy, fossil energy, coal, crude oil, and natural gas exploitation, processing, transportation, and power station operation processes. Power generation equipment was not within the scope of this study.

3.3.1.2. System boundary of nuclear power. The system boundary of nuclear power included the construction of basic infrastructure, nuclear fuel preparation, and the operational phase. The main considerations in the preparation of nuclear fuels include uranium melting and smelting, uranium conversion, enrichment, and component production.

3.3.1.3. System boundary of wind power. It is commonly accepted that the generation of wind energy itself does not consume energy or emit pollutants. Hence, in this study, the production of wind turbines and construction of infrastructure were included in determination of the environmental impacts of wind energy. This includes the production of basic construction materials (steel and concrete), towers, cabin hoods and blades, hubs, cabin chassis, generators, and gearboxes. Wind energy generators are designed to last for 20 years, averaging an annual runtime of 4500 h; this results in an accumulative generated energy of 81.54 GWh (Yang et al., 2015a, b).

3.3.1.4. System boundary of solar power. The generation of solar power does not produce environmental pollution or pollutants; however, the production process of photovoltaic equipment consumes a certain amount of resources and materials. This study took into account the entire production process, from the production of raw materials to the assembly of the photovoltaic equipment components. The process can be divided into six steps: silicon mining, industrial silicon production, solar energy grade polycrystalline silicon manufacturing, polycrystalline silicon disk manufacturing, battery production, and the assembly of photovoltaic equipment components. In this study,

Table 1
The math model for power grid optimization.

Factors		Thermal power *A*	Hydro power *B*	Wind power *C*	Nuclear power *D*	Solar power *E*
Environmental impacts	GHG	Ax	Bx	Cx	Dx	Ex
	WF	Ay	By	Cy	Dy	Ey
	MI	Az	Bz	Cz	Dz	Ez
Limitations	1、Range of power	$A \in$[Amin , Amax]	$B \in$[Bmin , Bmax]	$C \in$[Cmin , Cmax]	$D \in$[Dmin , Dmax]	$E \in$[Emin , Emax]
	2、$A + B + C + D + E$ = power consumption					
	3、The GHG, WF, and MI of optimized power are less than those before optimization					
Objective function	Minimum $F = \sum_{i=x,y,z} A_i + B_i + C_i + D_i + E_i$					

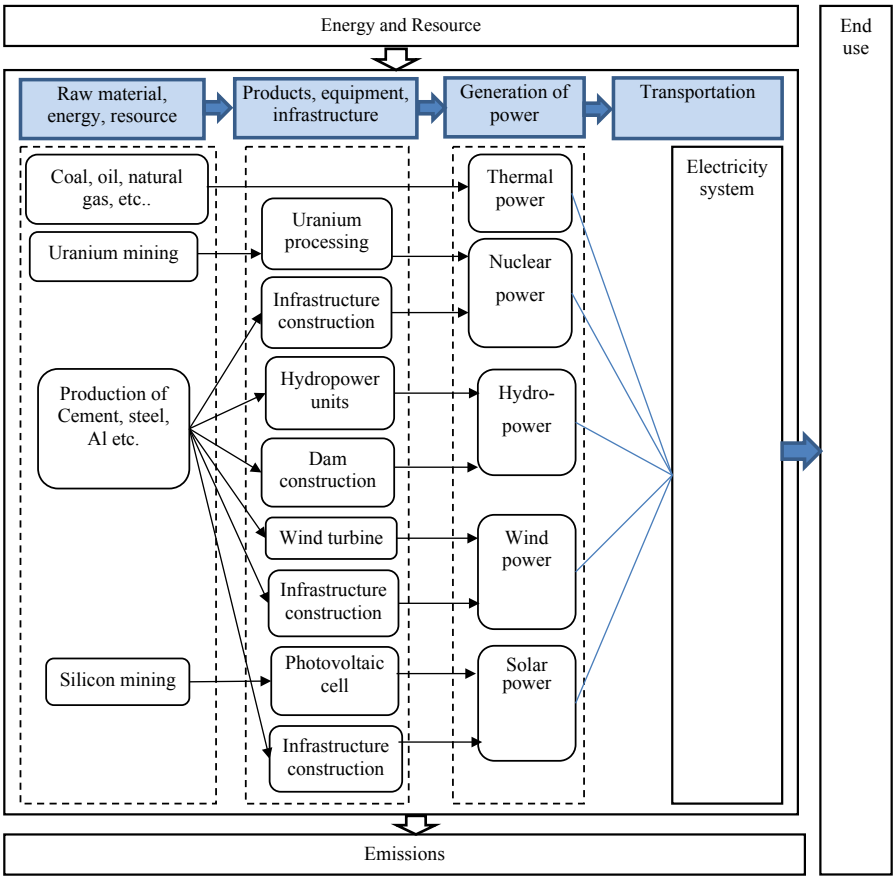

Fig. 2. System boundary of power system.

the service lifetime of solar power equipment was considered to be 30 years (Yang et al., 2015a, b).

3.3.1.5. System boundary of hydro power. The system boundary of hydro power included the ground excavation involved in dam construction, earth-rock filling, basic infrastructure construction, equipment supplies, material transport, and operational processes. As hydro power generation depends on seasonality and peak regulation effects, the operation of hydro power stations includes the use of thermal power.

3.3.2. Calculation of environmental impacts

3.3.2.1. Calculation of GWP. We previously calculated the GWP of these five power generation methods based on the system boundaries described above. This paper is a continuation of those efforts (Ding et al., 2017); refer to Table 2 for detailed results.

Table 2
The input materials for thermal power.

Energy input	Unit	Value
Raw coal	kg/kWh	4.59E-01
Cleaned coal	kg/kWh	1.50E-04
Other washed coal	kg/kWh	6.74E-03
Coke	kg/kWh	0.00E+00
Coke oven gas	m3/kWh	3.41E-03
Blast furnace gas	m3/kWh	2.47E-02
Converter gas	m3/kWh	2.46E-03
Crude oil	kg/kWh	2.79E-05
Diesel oil	kg/kWh	9.15E-05
Fuel oil	kg/kWh	1.11E-04
Petroleum coke	kg/kWh	–
Natural gas	m3/kWh	5.25E-03
Heat	MJ/kWh	9.61E-01

Table 3
The input materials for nuclear power, hydro power, wind power, and solar power.

Material and energy input	Nuclear power	Hydro power	Wind power	Solar power
Uranium element (kg/kWh)	5.43E-06	–	–	–
Silicon ore (kg/kWh)	–	–	–	2.79E-04
Cement (kg/kWh)	3.40E-03	9.45E-04	1.43E-03	–
Steel (kg/kWh)	1.08E-03	1.09E-03	1.78E-03	–
Glass (kg/kWh)	1.97E-05	–	–	9.34E-04
Cu (kg/kWh)	5.91E-05	–	–	–
Al (kg/kWh)	9.15E-07	–	–	2.39E-04
Paperboard (kg/kWh)	–	–	–	9.97E-05
HNO_3 (kg/kWh)	5.94E-04	–	–	–
H_2SO_4 (kg/kWh)	1.92E-06	–	–	–
Liquid nitrogen (kg/kWh)	6.90E-08	–	–	–
Zr (kg/kWh)	1.70E-06	–	–	–
Lime (kg/kWh)	1.28E-06	–	–	–
Nodular cast iron (kg/kWh)	–	–	5.87E-04	–
Polyester resin (kg/kWh)	–	–	6.97E-05	–
Epikote (kg/kWh)	–	–	4.18E-05	–
Fiberglass (kg/kWh)	–	–	1.32E-04	–
Hydrogen (kg/kWh)	–	–	–	1.20E-04
Chlorine (kg/kWh)	–	–	–	8.27E-05
Acetone (kg/kWh)	–	–	6.99E-06	–
Petroleum coke (kg/kWh)	–	–	–	6.25E-05
Coal (kg/kWh)	3.82E-04	–	–	1.01E-04
Thermal power (kWh/kWh)	5.01E-06	–	2.13E-04	1.83E-02
Diesel oil (kg/kWh)	–	2.95E-03	–	–
Steam (MJ/kWh)	–	–	–	1.49E-02

3.3.2.2. Calculation of WD. In previous research, we calculated the WD of the five types of power sources, based on the water footprint, using the environmental impacts method developed by Pfister (Pfister et al., 2009). We will use these previous calculations to determine the environmental impact of WD in the current study (Ding et al., 2017).

3.3.2.3. Calculation of MI. MI is used in reference to the total material requirements of a product during its life cycle, including material flow during usage and otherwise. In our study, the MI includes all direct MIs during the life cycle stages as well as indirect MIs.

For the calculation of MI, it is essential to include all input resources, with emphasis on two aspects (1) energy consumption (e.g., electricity): must be considered a “material” resource; (2) “inputs needed for input” and their respective MIs must be traced. For example, the coal input necessary for electricity input and the MI of coal itself, or the MI of iron ore input owing to the use of steel. In other words, the ideology of a product's life cycle is applied to calculate the MI.

According to this definition, the MI of power systems is calculated using equation (1).

$$M = M_d + M_i \quad (1)$$

where M denotes the MI of a given resource; M_d denotes a direct MI, including resource input and auxiliary resource input; and M_i denotes an indirect MI in the production of a given resource.

The calculation of the MI for power systems involves the cross-usage of different types of resources. For instance, the calculation of the MI of coal involves use of data from the MI of electricity production, and the calculation of the MI of electricity production itself involves the use of data from the MI of coal. This results in an iterative process. In this study, raw data were entered into the LCA software, SimaPro, to develop the model. Iterations were achieved using the model, ensuring accuracy of our data lists.

Table 4
Data sources in this study.

Items	Data sources
GWP of five types of power	Literature (Ding et al., 2017a, b)
WD of five types of power	Literature (Ding et al., 2017a, b)
MI of five types of power	Literature (Hu et al., 2013; Jiang et al., 2015; Yang et al., 2015a, b; Yang, Liu et al. 2015, 2015; Ding et al., 2017a, b)
The normalization factors	Method report (Goodkoop, 1999)

Table 5
The environmental impacts of power systems.

Environment impacts	Thermal power	Hydro power	Solar power	Nuclear power	Wind power
MI (kg/kWh)	0.5	0.005	0.026	0.006	0.004
GWP(g/kWh)	1045.68	15.68	53.37	6.36	8.49
WD (m^3/kWh)	1.19	6.75	5.3	0.19	0.14

The MI of power includes the direct input of resources, as well as indirect input resulting from the input resources. Direct MI includes natural resources and other auxiliary materials, which are listed in Tables 2 and 3.

3.3.3. Data sources

The inventory compilation of MI, GWP, and WD requires a large amount of data. In this study, most of the data used were acquired from industrial reports and published academic literature. The data sources used in our study are listed in Table 4.

3.4. Normalization of the three kinds of environmental impacts

In terms of the three mid-point environmental impact categories selected by the optimization model, through combining MI and Eco-indicator 99 inventory analysis, we selected two aspects of fossil fuels and mineral resources to represent the MI to power systems. Using SimaPro, we determined the environmental impact using GWP and MI, and then determined the ultimate ecological indicators.

WD is considered as a midpoint category in life cycle impact assessment. It is obtained by the product of water consumption and the characterization factor. The characterization factor for WD is the water stress index (WSI). First, we calculated the water resource depletion based on China's WSI, a water resource characterization factor (0.78). Then, using the provided normalization factor (0.45), we normalized the depletion of water resources to the ultimate environmental impact of ecosystem damage. Lastly, based on the weighting factor provided in the study (0.53) (Pfister et al., 2009), we derived an ultimate ecological index.

4. Results

4.1. Environmental impact analysis

4.1.1. Environmental impact analysis of MI/WD/GWP of power system

Three types of environmental impacts resulting from the different types of power in China are shown in Table 5. An analysis of MI shows that in China, thermal power requires the greatest resource input, followed by solar power and then nuclear power. An analysis of GWP reveals that thermal power also has the greatest emissions, followed by solar power and then nuclear power. An analysis of WD shows that hydro power has the largest footprint, followed by solar power and then wind power. On the basis of these three types of environmental impacts, it appears that wind power and nuclear power are somewhat better for

Table 6
The normalization results of power systems.

Environment impacts	Thermal power	Hydro power	Solar power	Nuclear power	Wind power
MI (Pt/kWh)	2.67E-02	1.64E-04	1.33E-03	1.01E-04	9.81E-05
GWP(Pt/kWh)	5.68E-03	8.52E-05	2.90E-04	3.46E-05	4.61E-05
WD (Pt/kWh)	1.47E-04	8.35E-04	6.55E-04	2.35E-05	1.73E-05
The total	3.52E-02	1.08E-03	2.28E-03	1.59E-04	1.62E-04

Table 7
Optimization results for power grid.

Power	Thermal power	Hydro power	Solar power	Nuclear power	Wind power
Before optimization	78.74%	17.16%	0.07%	1.97%	2.06%
After optimization	55.16%	14.68%	0.07%	22.52%	7.57%

Table 8
Reduction in environment impacts.

Environmental impacts	Reduction in amount	Reduction in portion
MI (kg)	5.8116E+11	29.53%
GHG (g)	1.2224E+15	29.67%
WD (m3)	2.0009E+12	19.06%

the environment.

In 2012, the electricity demand in China was 49859 hundred million kWh, where thermal, hydroelectric, nuclear, wind, and solar power were used to supply 78.74%, 17.16%, 1.97%, 2.06%, and 0.07% of this demand, respectively. Based on these power structures, the total MI, GWP, and WD for power generation in China was 19.6 hundred million t, 41.2 hundred million t $CO_{2\text{-eq.}}$, and 104647 hundred million m^3, respectively.

4.1.2. Normalization of environmental impact

The results obtained from the normalization method in Section 3.4 are listed in Table 6. In Table 5, we can compare the environmental impacts of the different kinds of power. After normalization, we can compare different environment impacts for one kind of power. It can be seen that MI is the main environmental problem instead of GWP for all kinds of power, except hydro power.

This indicates that all kinds of power generate a burden on natural resources. The power industry is heavily reliant on natural resources. Thermal power depends on fossil fuels, coal, natural gas, etc.. Nuclear power depends primarily on uranium. Although solar power and wind power use renewable resources, the machines and infrastructure required for generation of solar and wind power also require a significant amount of materials and minerals.

There are different characteristics of GWP and WD for the different kinds of power. For thermal power, GWP is greater than WD; for hydro power, WD is greater than GWP.

4.2. Results of power structure optimization

Program operation analysis in Matlab was used to obtain the power structure optimization results, as depicted in Table 7. The results show that the ratio of thermal power decreased significantly, the ratio of hydro power decreased by ~3%, the ratio of solar power remained stable, the ratio nuclear power increased significantly, and the ratio of wind power increased by ~5%.

The potential for decreasing the environmental impact of these types of power structures is shown in Table 8. Compared to the original structures, MI, GWP, and WD can be decreased by 29.53%, 29.67%, and 19.06%, respectively, by the optimized power structure. This shows that structural adjustment to power systems in China has considerable potential for saving resources and decreasing emissions.

With an optimized power structure, MI and GWP would decrease by ~30% each. The potential decrease in GWP with optimization of China's power structures is 12.2 hundred million tons. A further reduction in emissions can be achieved if we decrease the input of coal for generating thermal power and increase power generation using natural gas.

With respect to WD, there is potentially a 19% energy saving with the optimized structure. For MI and GWP, the “renewable” power sources, i.e., hydro power and solar power, are less advantageous than thermal power. These renewable power sources have a limited potential for decreasing WD, and the WD for these power sources greatly exceeds that of thermal power.

5. Discussion

5.1. Optimization results in our study

The optimization results provide new knowledge for planning and adjustments to the power industry. According to the results in Table 7, the percentage of thermal power used should be decreased. In fact, the thermal power industry is a major contributor to national resource consumption and pollutant emissions; the percentage of thermal power is planned to decrease, but it remains a large contributor to the power industry development strategy.

The development of large-scale hydro power stations, nuclear power plants, etc., can directly optimize power structures and facilitate emissions reductions in China; this will yield significant environmental benefits. That being said, the development of non-fossil fuel sources is limited by the ecological environment, technological advancements, and budget constraints. There is potential for resource development in China, but the development of hydro power is limited by immigration and social issues, and the seasonal nature of hydro power generation renders its large-scale development in China difficult. The development of wind and solar power is restricted by development costs and the lack of technical skills. The lack of significant increase in the use of non-fossil fuels in the mid-term reflects a number of difficulties that are yet to be overcome.

According to the optimization results, the percentages of hydro power, nuclear power, and wind power can increase to a certain level, but not enough for large scale. Therefore, the optimization results obtained in this study are consistent with the general situation of power generation in China.

5.2. Limitations of this model

This model can optimize energy structures under different environmental impacts based on the LCA method. LCA provides a novel method and premise for energy structure optimization. As such, the environmental impacts covered by the current model must be in accordance with the LCA environmental impacts. Other problems, such as ecology system service function, ecology toxicity, etc., are not covered

by the LCA model; thus, the LCA model is not suitable for investigation of these types of problems. A more comprehensive method for consideration of other eco-environmental issues should be addressed in the future.

This study is only an integrative investigation into the optimization of power structures with different types of environmental impacts. It provides a logical model for the evaluation of environmental impacts and serves as a comprehensive method to aid in resource development planning. While ensuring adequate resource supply, it also aims to decrease the environmental burden caused by resource supply. The optimization of energy structures in China should integrate different influential factors, particularly environmental impacts, to simultaneously maintain energy supply while minimizing environmental impacts.

6. Conclusions

A novel application of LCA methodology for optimization of power structures has been developed in this study. This method provides new insight into optimization of energy structures by considering different environment impacts.

(1) This study established a model for the optimization of power structures under the limitations of multi-environment impacts such as MI, GWP, and WD, unlike previous studies that have only considered carbon emissions. This study integrated the evaluation of environmental impacts based on LCA into the optimization model, providing a basis for new considerations and methods for the development of optimized energy structures.
(2) The applicability of the proposed methodology is demonstrated through the case study of the China power sector. It is interesting to note that nuclear power plays a critical role in the optimal power mix, followed by wind power. The total environmental impacts were reduced; MI, GWP, and WD were decreased by 29.53%, 29.67%, and 19.06%, respectively.

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